

# Machine Learning Flavour Tagging for Future Higgs Factories

Mareike Meyer

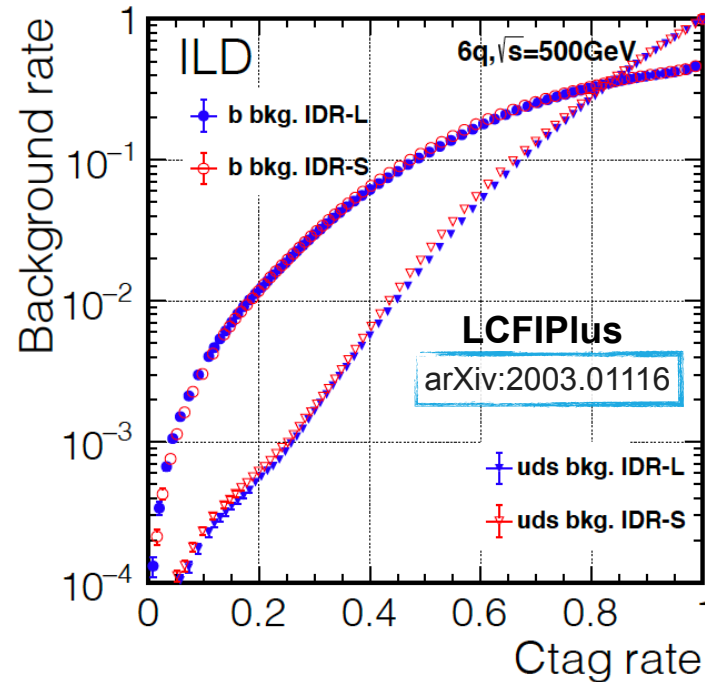
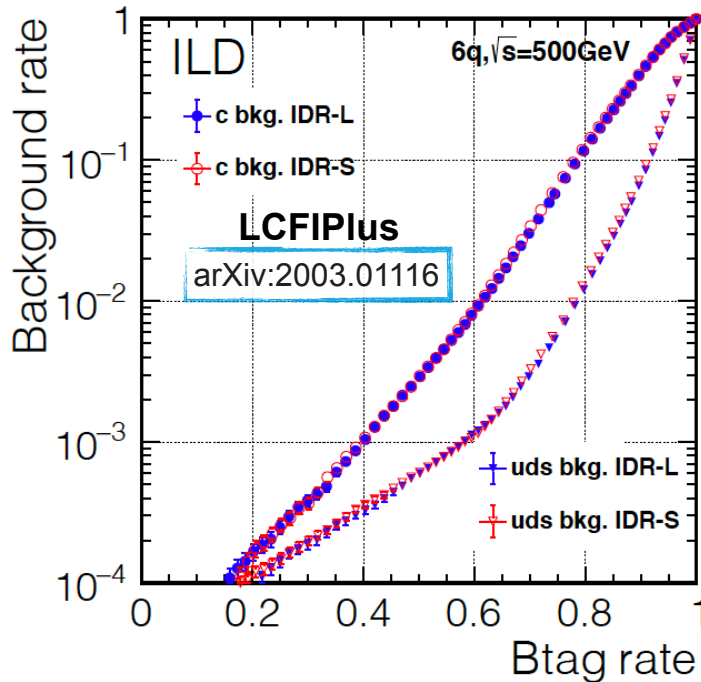
Second ECFA Workshop on e<sup>+</sup>e<sup>-</sup> Higgs/EW/Top Factories, 12/10/2023



# Introduction

- **current standard** for heavy flavour tagging at ILD: **LCFIPlus**
- based on TMVA (BDTs)

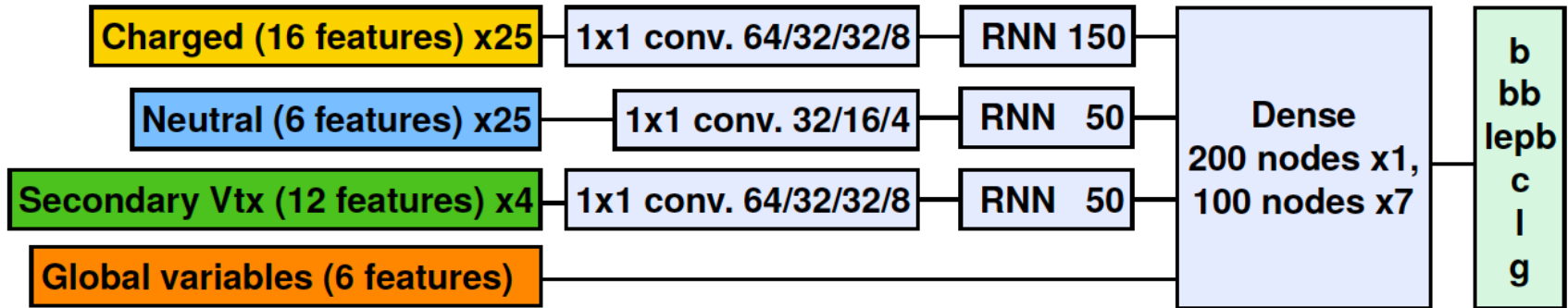
arXiv:1506.08371,  
<https://github.com/lcfiplus/LCFIPlus>



- ➔ Can the **heavy flavour tagging** be improved by replacing the BDTs used in LCFIPlus with (deep) NNs?

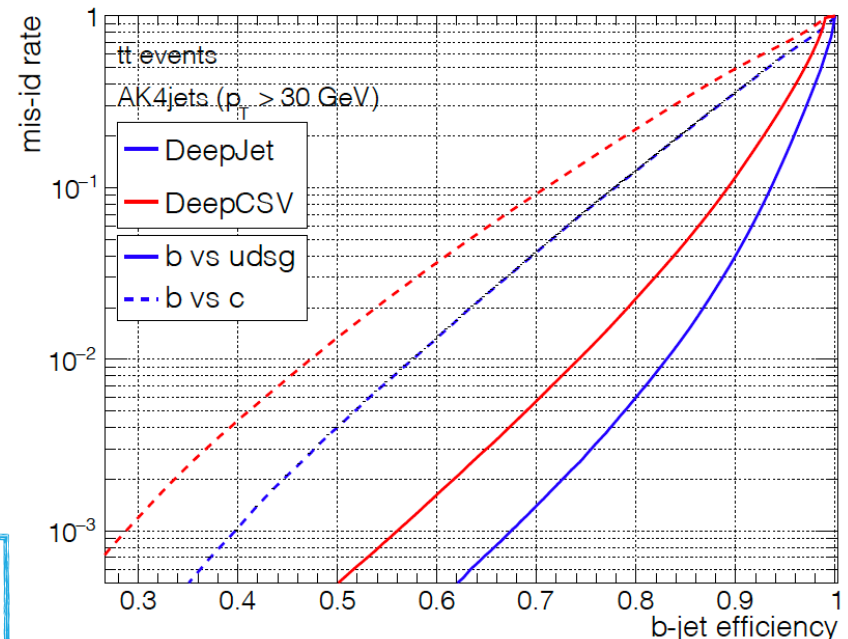
**this work:** application of CMS DeepJet and ParticleNet to ILD

# CMS DeepJet



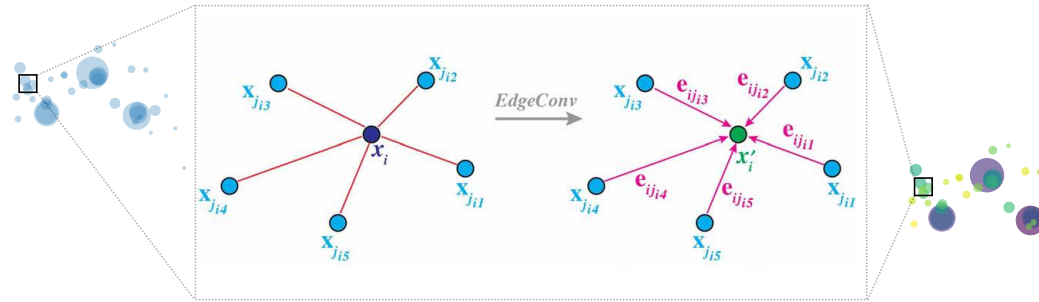
- successfully applied in many CMS analyses
- allows for **usage of low-level features** from **many jet constituents**
- able to deal with **variable length of inputs**
- allows for **ordering** of particles **according to** their assumed **importance**
- **large gain in performance** compared e.g. to FCNN (DeepCSV)

*Jet Flavour Classification Using DeepJet arXiv:2008.10519, Identification of heavy-flavour jets with the CMS detector in pp collisions at 13 TeV arXiv:1712.07158*



# ParticleNet

arXiv:1902.08570, *Pushing the Limit of Jet Tagging With Graph Neural Networks*, Huilin Qu, talk at ML4Jets2021, July 7, 2021



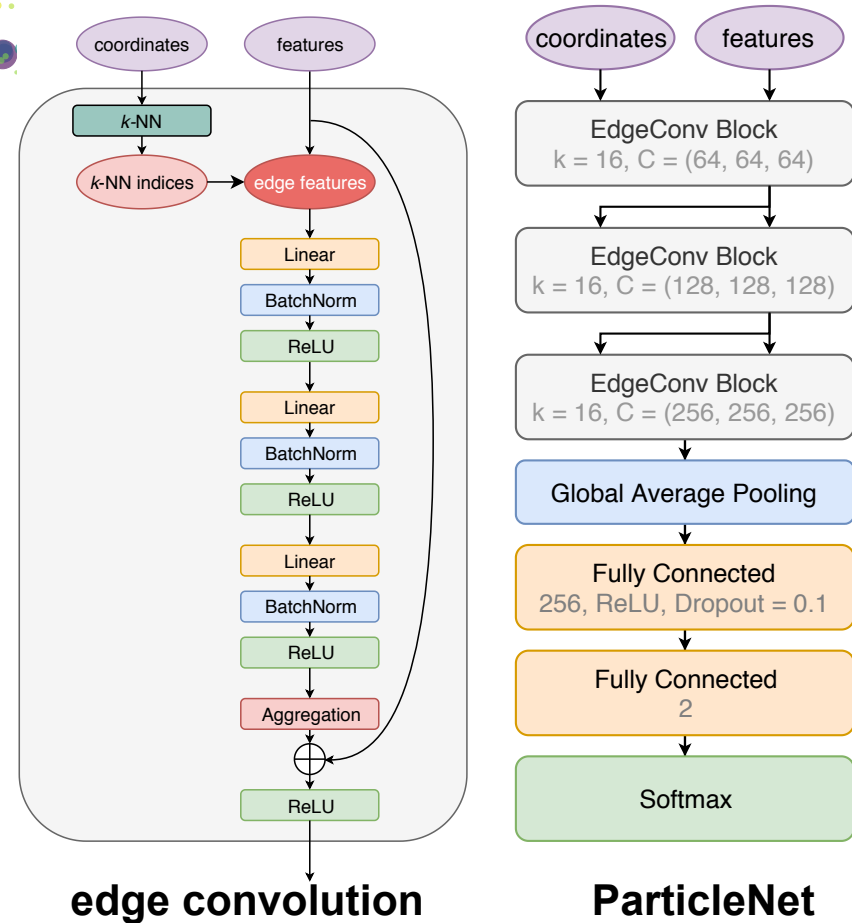
- treat jet as „particle cloud“
- input: **jet constituents**

key building block: **edge convolution**

- particle cloud: graph, each point: vertex, connections between each point & k nearest neighboring points: edges
- learn an „**edge feature**“ for each pair:

$$e_{ij} = \text{MLP}(x_i, x_j)$$

- **MLP**: parameters **shared among all edges**
- **aggregation** of edge features:  $x'_i = \text{mean}_j e_{ij}$



# Training data & data pre-processing

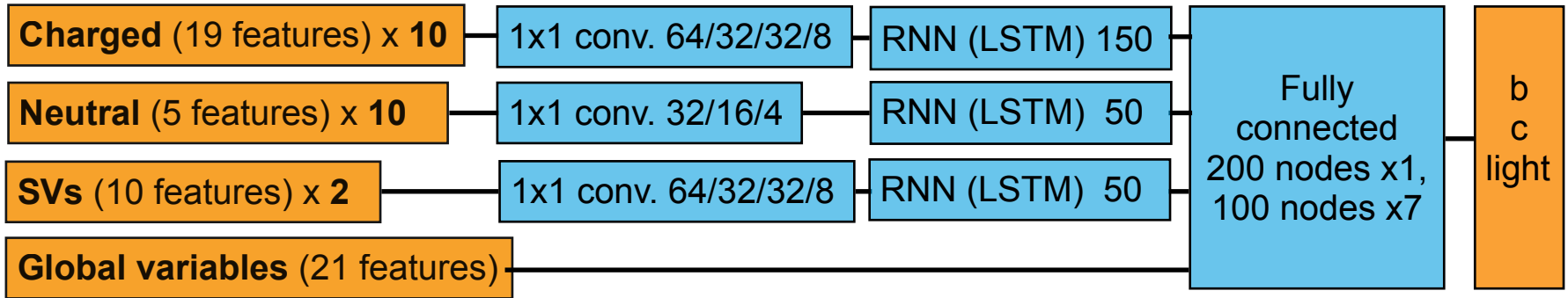
- study **events with 6 jets** (b,c,u,d,s)
  - 1 : 1 : 3 for b : c : light
- run PV & SV finder, jet clustering and vertex refinement of LCFIPlus
- **split sample** into training, validation and test (75% / 12.5% / 12.5%)
- **training data**: oversampling of b & c jets performed to get same number of b,c & light jets
  - ➔ ~4.3 Mio. jets in total
- **validation data**: keep original composition (1 : 1 : 3 for b : c : light)
  - ➔ ~394.000 jets in total

## data pre-processing:

- if a value of a features is not available, the value is set to -10
- **normalize input features** to mean 0, std 1

# DeepJet

# DeepJet: architecture



- classify jets into **three classes**: b jets, c jets & light jets
- **ordering of input particles** by (as applied in CMS)
  - impact parameter significance for charged jet constituents
  - shortest angular distance to a secondary vertex (by momentum if there is no secondary vertex) for neutral jet constituents
  - flight distance significance for secondary vertices

# DeepJet: input features

## global variables

$p^{\text{jet}}$ ,  $p_{\text{T}}^{\text{jet}}$ ,

$N_{\text{charged jet const.}}$ ,  $N_{\text{neutral jet const.}}$ ,  $N_{\text{SV}}$

additional global variables from LCFIPlus

**21 input features**

## charged jet constituents

$p^{\text{track}}/p^{\text{jet}}$ ,  $p_{\text{T}}^{\text{track}}$  (rel. jet),  $\vec{p}^{\text{track}} \cdot \vec{p}^{\text{jet}}/p^{\text{jet}}$

$\Delta R(\text{track}, \text{jet})$

impact parameter & significances

track reconstructed in PV?

lepton related variables

pid variables

$\chi^2/\text{ndf}$

**19 input features**

## neutral jet constituents

$p^{\text{neutral const.}}$ ,  $p^{\text{neutral const.}}/p^{\text{jet}}$

$\Delta R(\text{jet}, \text{neutral const.})$

is photon?

$E_{\text{HCAL}}/E_{\text{HCAL}+\text{ECAL}}$

**5 input features**

## secondary vertices

$m_{\text{SV}}$

$N_{\text{tracks in SV}}$

$\Delta R(\text{SV}, \text{jet})$

$E_{\text{SV}}/E_{\text{jet}}$ ,  $E_{\text{SV}}$

$\cos(\text{flight direction}_{\text{SV}}, \vec{p}_{\text{SV}})$

3D IP and significance

$\chi^2$ ,  $\text{ndf}$

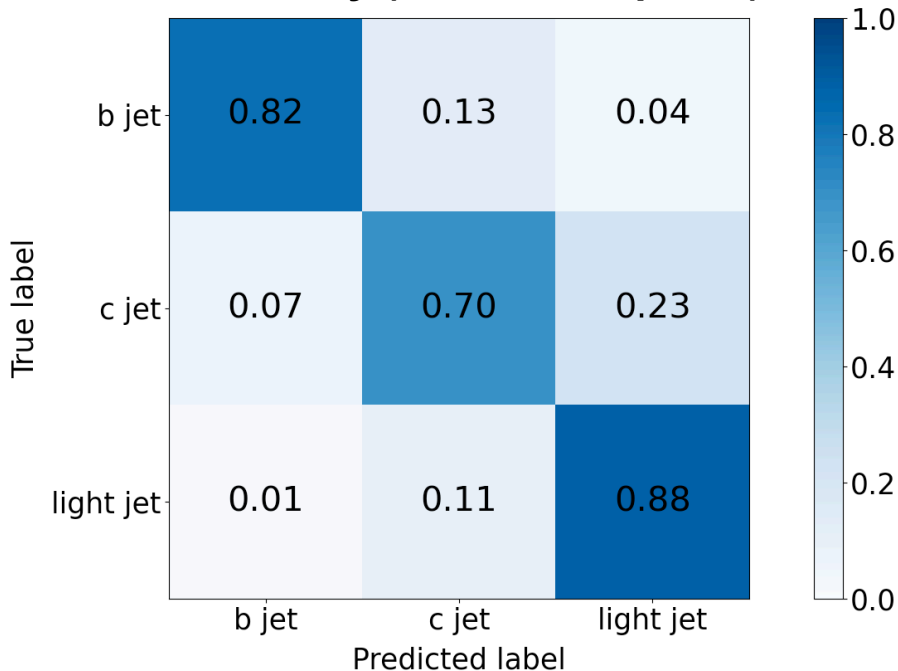
**10 input features**



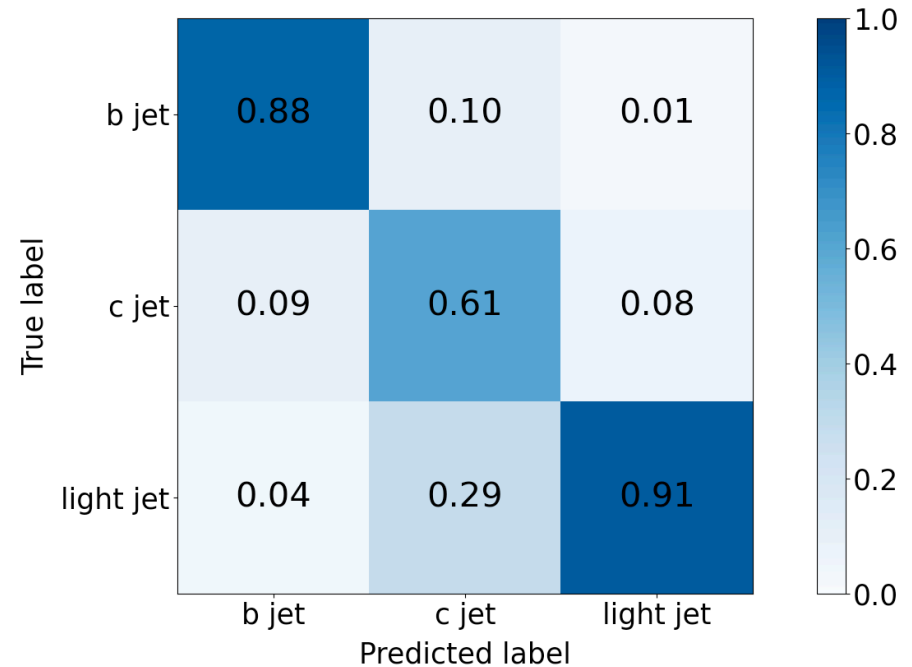
# DeepJet: confusion matrices

validation data

efficiency (rows sum up to 1)



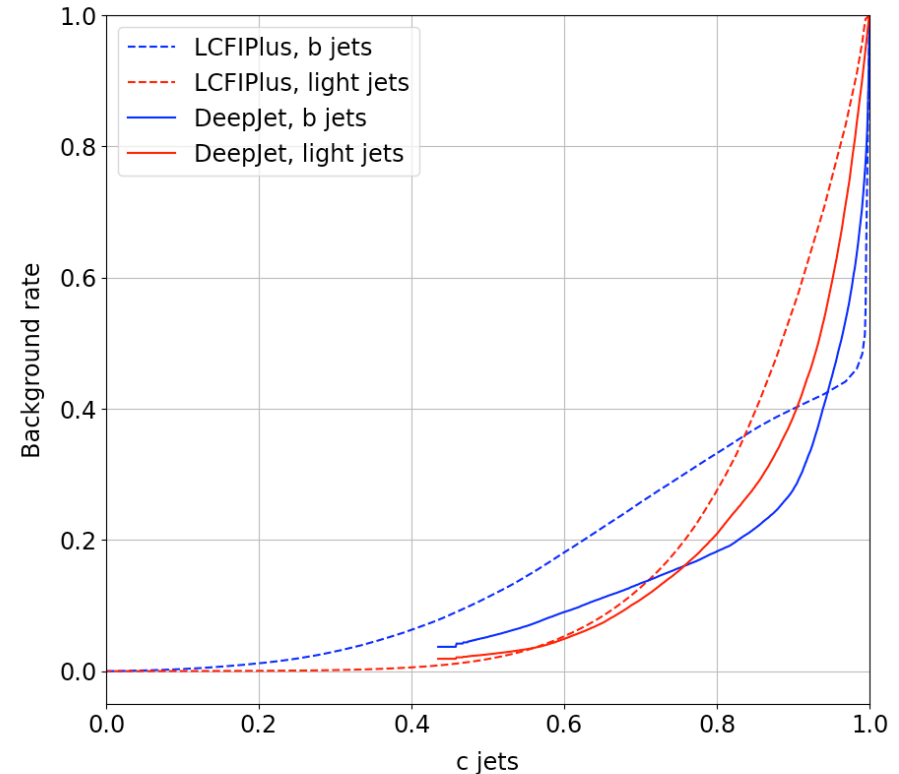
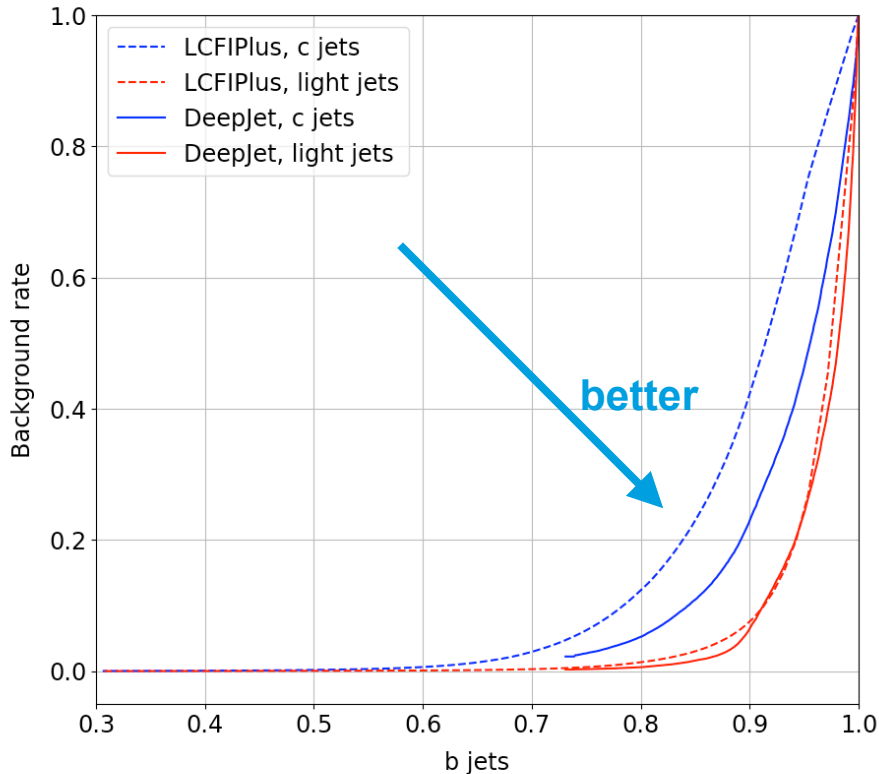
purity (columns sum up to 1)



- identification **efficiencies of over 82% for b jets & light jets**
- **c jet** identification **efficiency** lower (**70%**)
- especially **separation between c jets and light jets should be improved**

# DeepJet: ROC curves - comparison to LCFIPlus

validation data



**better performance of DeepJet training over large parts of the b & c tagging efficiencies w.r.t default LCFIPlus used in ILD**

# ParticleNet

# ParticleNet: input features

## jet constituents: coordinates

$\Delta\eta, \Delta\Phi$

## jet constituents: features

$\Delta\eta, \Delta\Phi$

$\log(p_T), \log(E), \log(p_T/p_T^{\text{jet}}), \log(E/E^{\text{jet}}),$   
 $\vec{p}^{\text{track}} \cdot \vec{p}^{\text{jet}}/p^{\text{jet}}$

$\Delta R$

$q$

isElectron, isMuon, isChargedHadron,  
isNeutralHadron, isPhoton

impact parameter & significances

track used in PV?

lepton related variables

pid variables

$E_{\text{HCAL}}/E_{\text{HCAL}+\text{ECAL}}$

$\chi^2/\text{ndf}$

**28 input features**

## secondary vertices: coordinates

$\Delta\eta, \Delta\Phi$

## secondary vertices: features

$\Delta\eta, \Delta\Phi$

$\log(p_T), E_{\text{SV}}/E_{\text{jet}}, E_{\text{SV}}$

$\eta$

$m_{\text{SV}}$

$N_{\text{tracks in SV}}$

$\chi^2/\text{ndf}$

impact parameters & significances

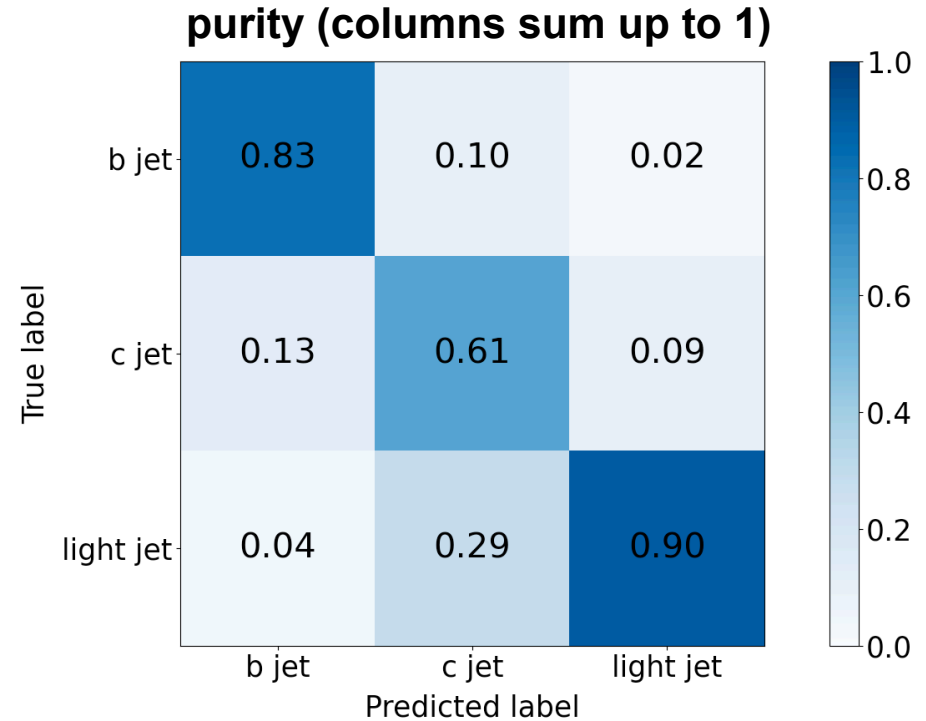
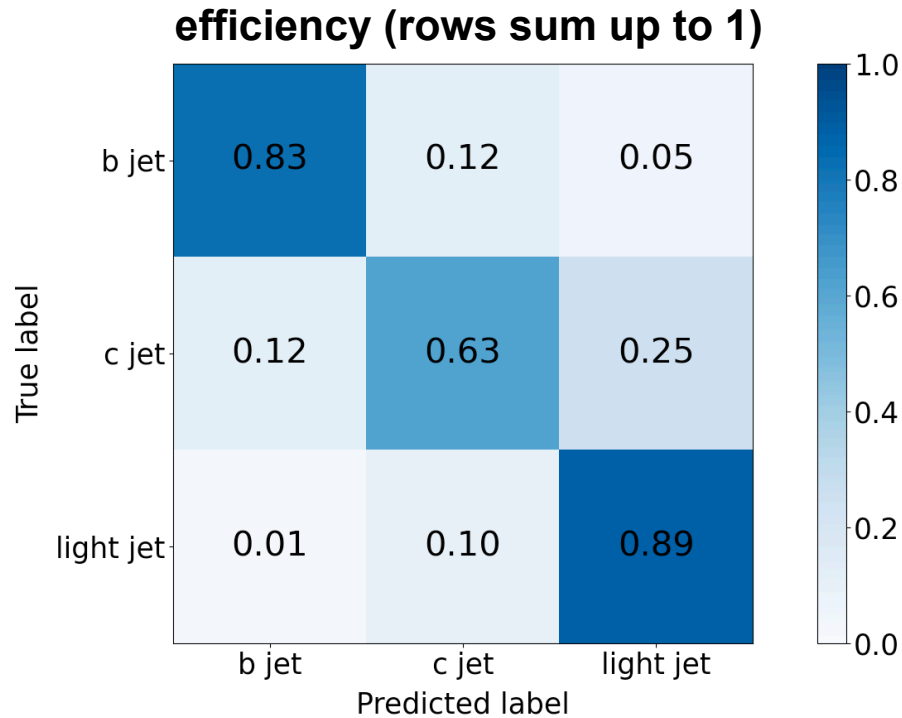
$\cos(\text{flight direction}_{\text{SV}}, \vec{p}_{\text{SV}})$

**14 input features**

**2 SVs & all jet constituents  
considered, no ordering of inputs**

# ParticleNet: confusion matrices

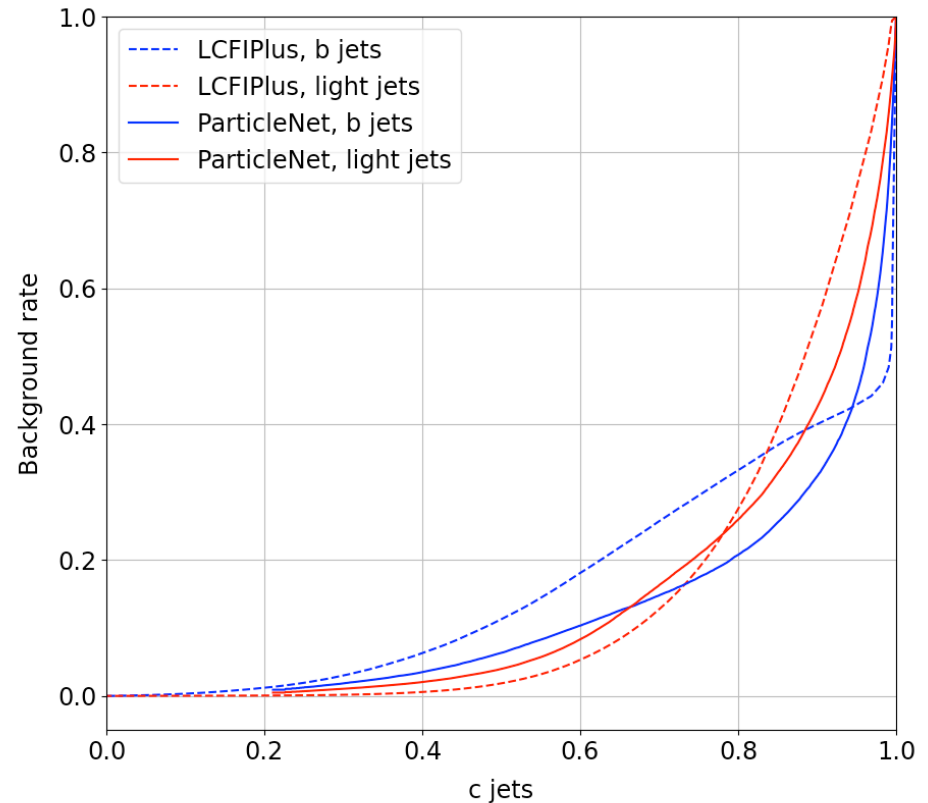
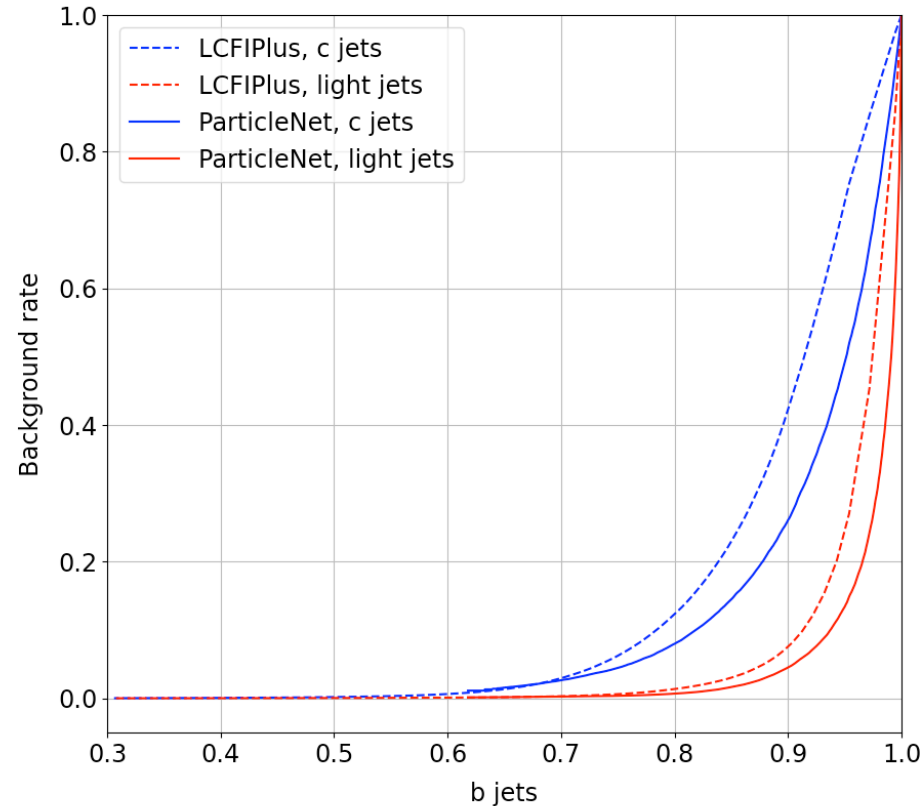
validation data



- identification **efficiencies of over 83% for b jets & light jets**
- **c jet** identification **efficiency** quite low (**63%**)
- especially **separation between c jets and light jets should be improved**, larger confusion of c jets with b jets than with DeepJet training

# ParticleNet: ROC curves - comparison to LCFIPlus

validation data

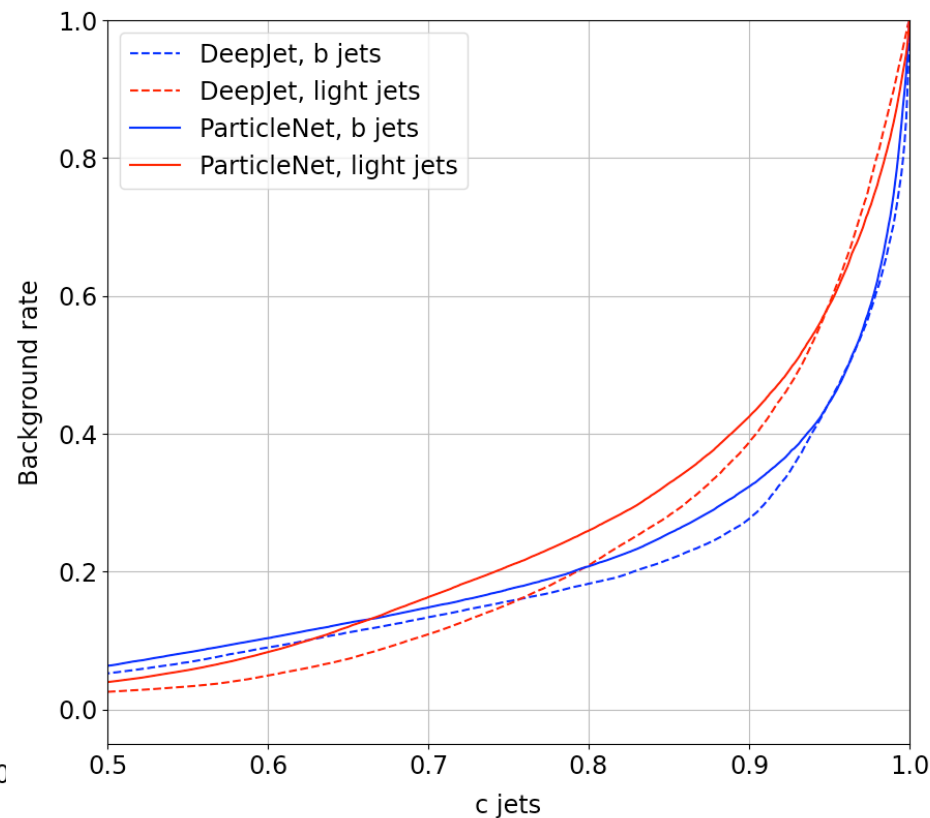
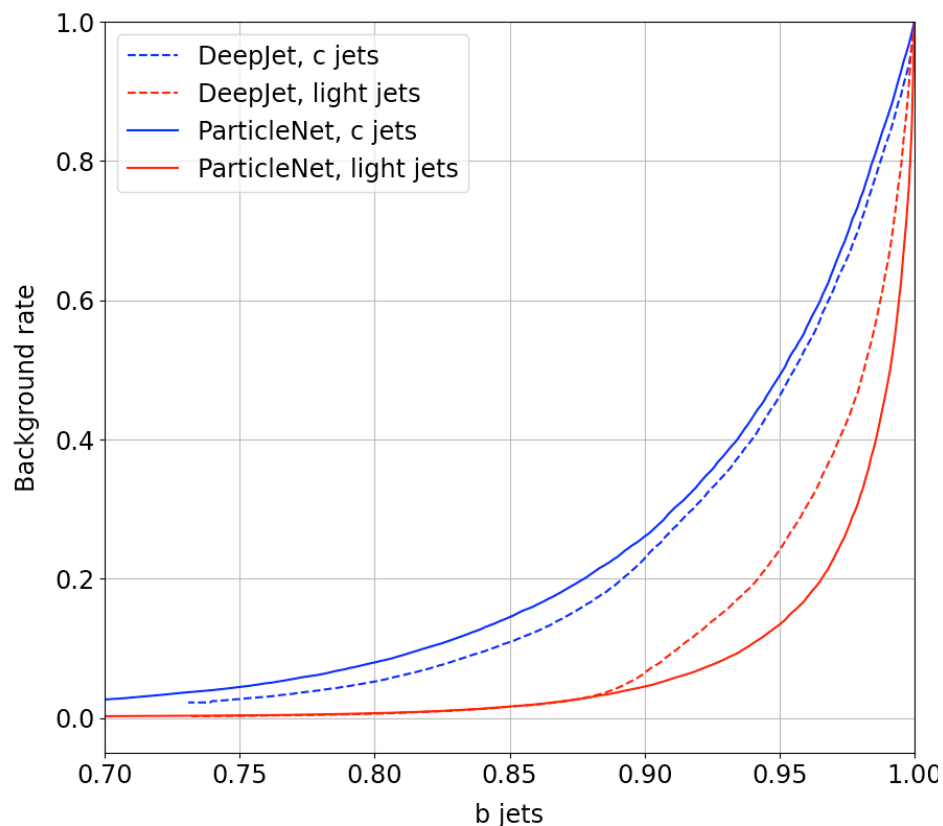


**better performance than LCFIPlus over large parts of the b and c tagging efficiencies**

**one of the first trainings with this architecture, a lot of possibilities for optimization**  
(architecture, hyperparameters, features, over-training in c-jet category...)

# ParticleNet: ROC curves - comparison to DeepJet

validation data



**better performance with DeepJet for b vs. c identification and for c vs. b & light jet identification**

**better performance of ParticleNet for b jet vs. light jet identification**

# Summary & outlook

- application of **CMS DeepJet** tagger and **ParticleNet** to **ILD**
- **(large) improvements in b and c jet identification vs. c/b and light jet background** w.r.t. default LCFIPlus used in ILD
- **ParticleNet model not yet optimized**
  - ➔ a lot of possibilities to further improve performance

## Outlook:

- **further optimization** of ParticleNet model
- study **performance on different processes**
- study **s-tagging efficiency**
- integrate into **iLCSoft/Key4hep** to make the taggers usable for others

**Thank you for your attention!**



# Backup

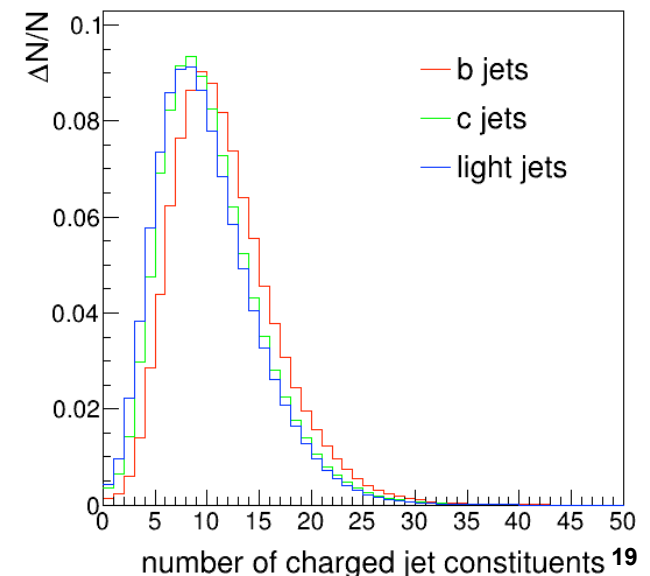
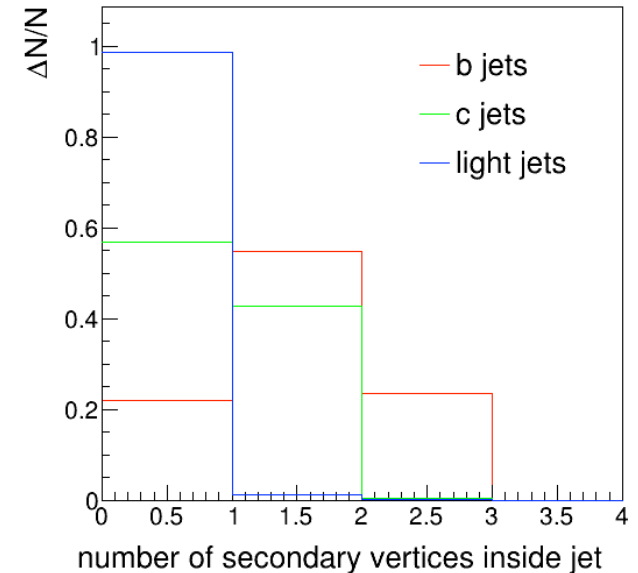
# Training data: details

- study **events with 6 jets** (b,c,u,d,s)
  - /pnfs/desy.de/ilc/prod/ilc/mc-opt-3/ild/dst-merged/500-TDR\_ws/flavortag/ILD\_I5\_o1\_v02/v02-00-01/
- run PV & SV finder, jet clustering and vertex refinement of LCFIPlus
- split sample into training, validation and test (75% / 12.5% / 12.5%)
- number of jets in **training data**:
  - b jets: 434116
  - c jets: 484034
  - light jets: 1449546
  - ➔ over-sampling of b and c jets performed to get same number of b,c & light jets
  - ➔ **total number of jets in training data**:  $3 * 1449546 = 4348638$
- number of jets in **validation data**:
  - b jets: 72443
  - c jets: 80890
  - light jets: 241283

# DeepJet: input features - global variables

21 input features

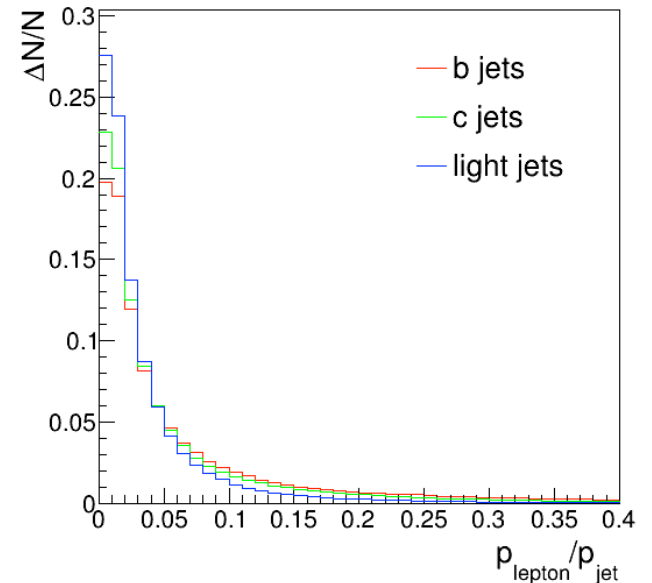
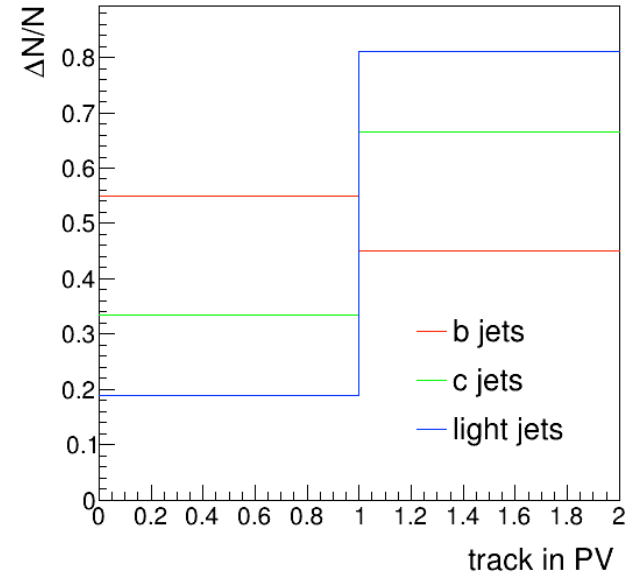
- jet momentum
- jet transverse momentum
- number of charged jet constituents
- number of neutral jet constituents
- number of secondary vertices
- additional variables from LCFIPlus:
  - mass of all tracks with  $d_0/z_0$  significance  $> 5\sigma$
  - product of b/c/light-quark probabilities of  $d_0/z_0$  values of all tracks, using b/c/light-quark  $d_0/z_0$  distributions
  - joint probability in the  $r$ - $\phi$  plane / in the  $z$  projection using all tracks (with IP significance  $> 5\sigma$ )
  - vertex probability taking into account all tracks associated to vertex
  - distance and its significance between the first and second vertex in the jet
  - mass of the vertex (pT - corrected)
  - vertex probability of all vertices



# DeepJet: input features - charged jet constituents

- track momentum / jet momentum
- transverse track momentum relative to jet
- dot product of jet and track momentum w.r.t. jet momentum
- $\Delta R(\text{track}, \text{jet})$ ,
- $d_0$ ,  $d_0$  significance
- $Z_0$ ,  $Z_0$  significance
- 3D impact parameter, 3D impact parameter significance
- track reconstructed in PV?
- is electron?, is muon?, lepton momentum relative to jet, lepton transverse momentum relative to the jet, lepton momentum / jet momentum
- kaon-ness of charged particles, track momentum fraction weighted with kaon-ness
- $\chi^2/\text{ndf}$

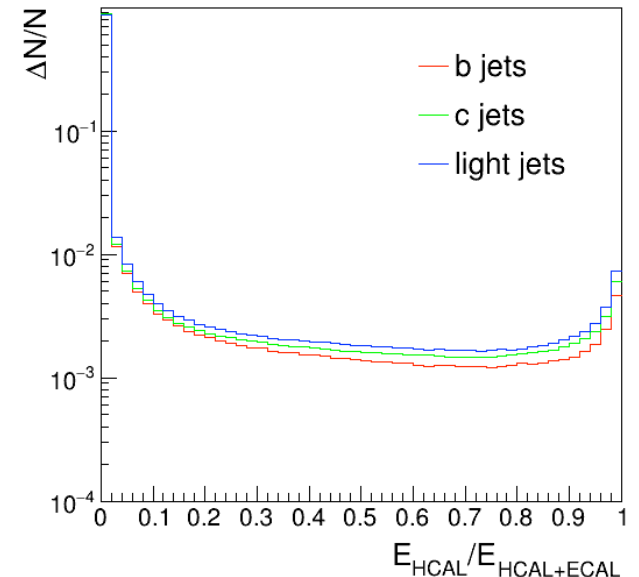
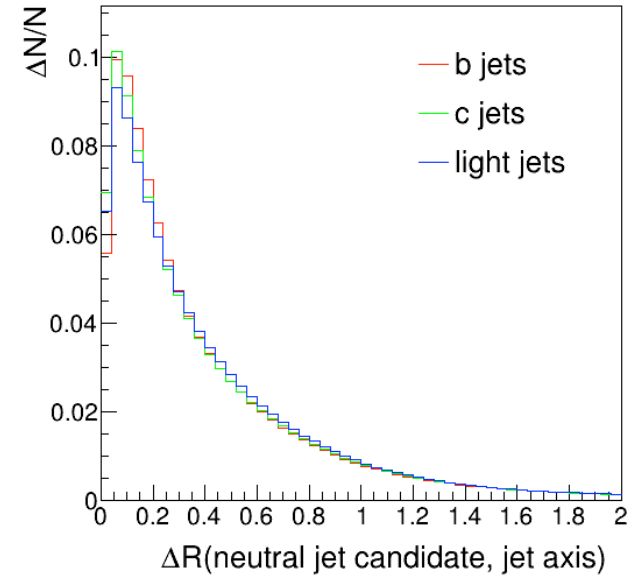
19 input features



# DeepJet: input features - neutral jet constituents

- momentum of neutral jet constituent
- fraction of the jet momentum carried by neutral jet constituent
- $\Delta R(\text{jet axis, neutral candidate})$ ,
- is photon?
- fraction of neutral candidate energy deposited in the hadronic calorimeter

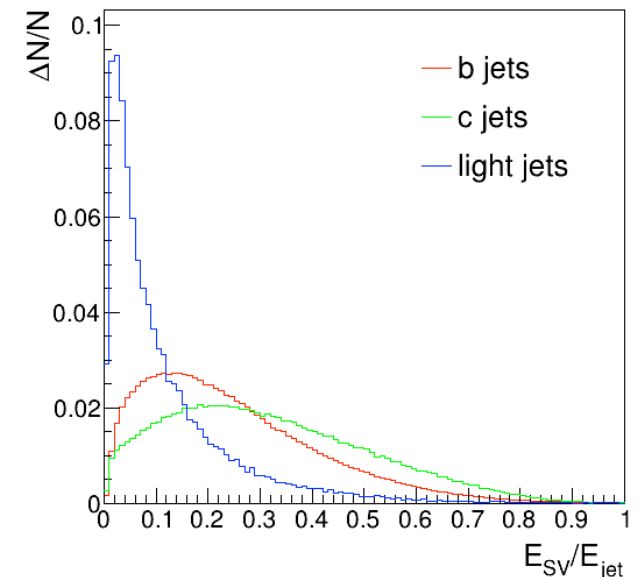
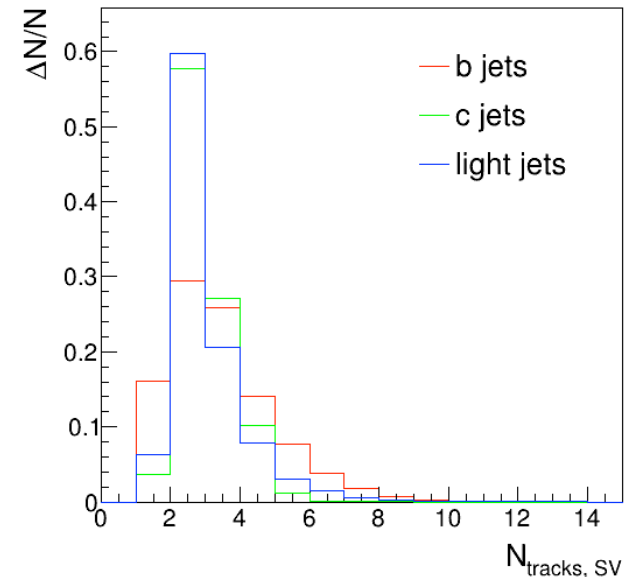
5 input features



# DeepJet: input features - secondary vertices

- SV mass
- number of tracks in SV
- $\Delta R(\text{SV, jet})$
- SV energy / jet energy
- SV energy
- cosine of the angle between the secondary vertex flight direction and the direction of the secondary vertex momentum
- 3D impact parameter, 3D impact parameter significance
- $\chi^2$ , ndf

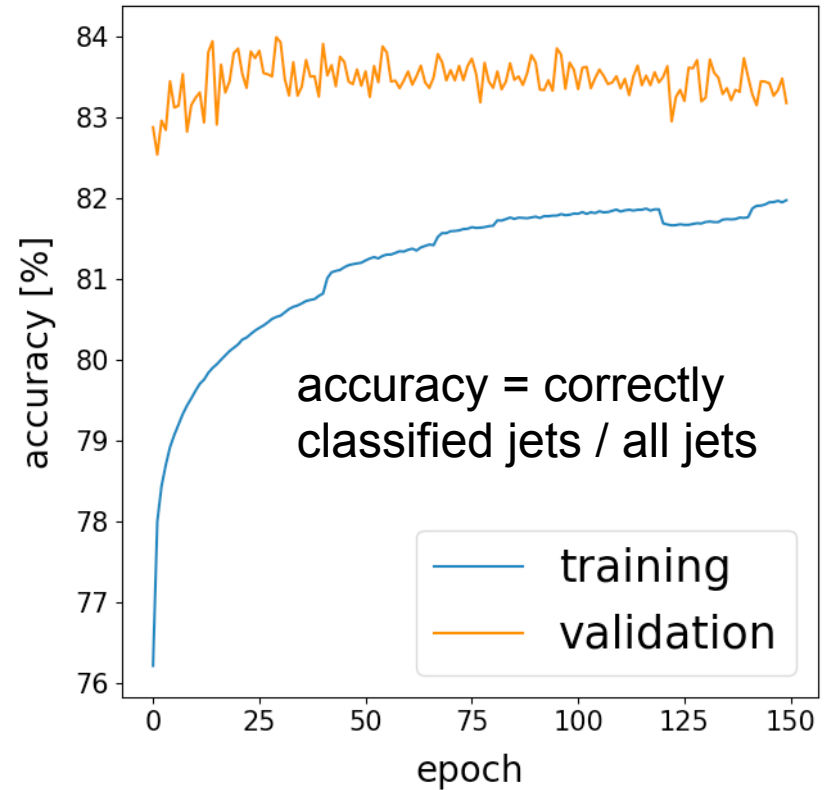
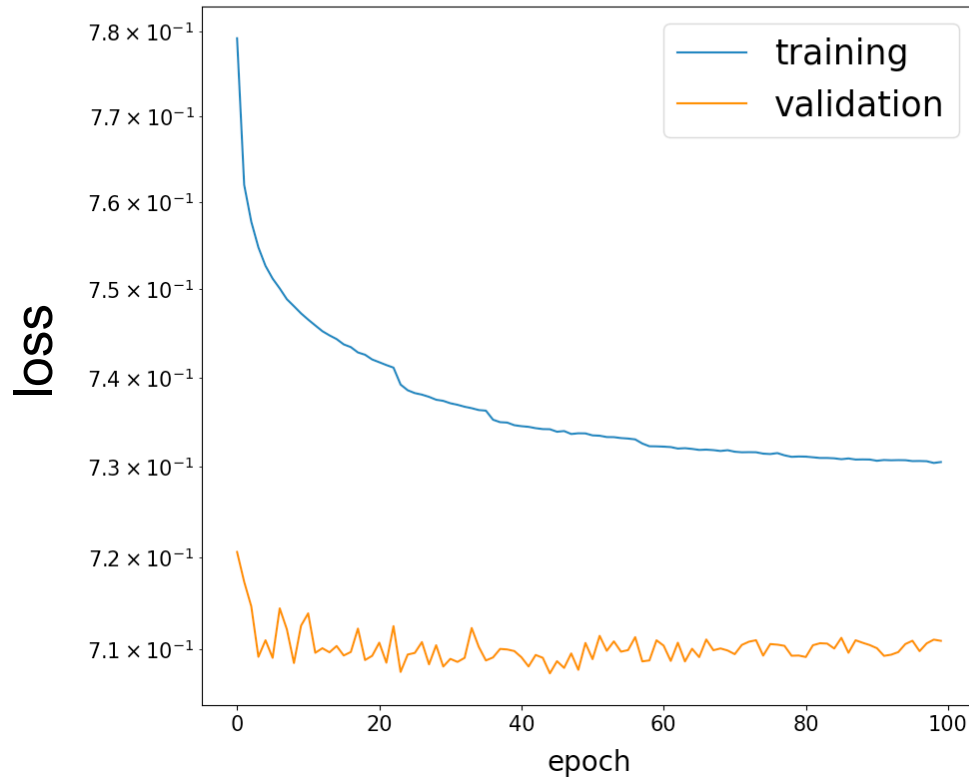
10 input features



# DeepJet: training

- activation functions: relu / softmax (last layer)
- cross entropy loss
- optimizer: Adam
- regularization: batch normalization, dropout (0.1)
- batch size: 200
- learning rate: 0.0003
- number of epochs: 100
- Xavier weight initialization

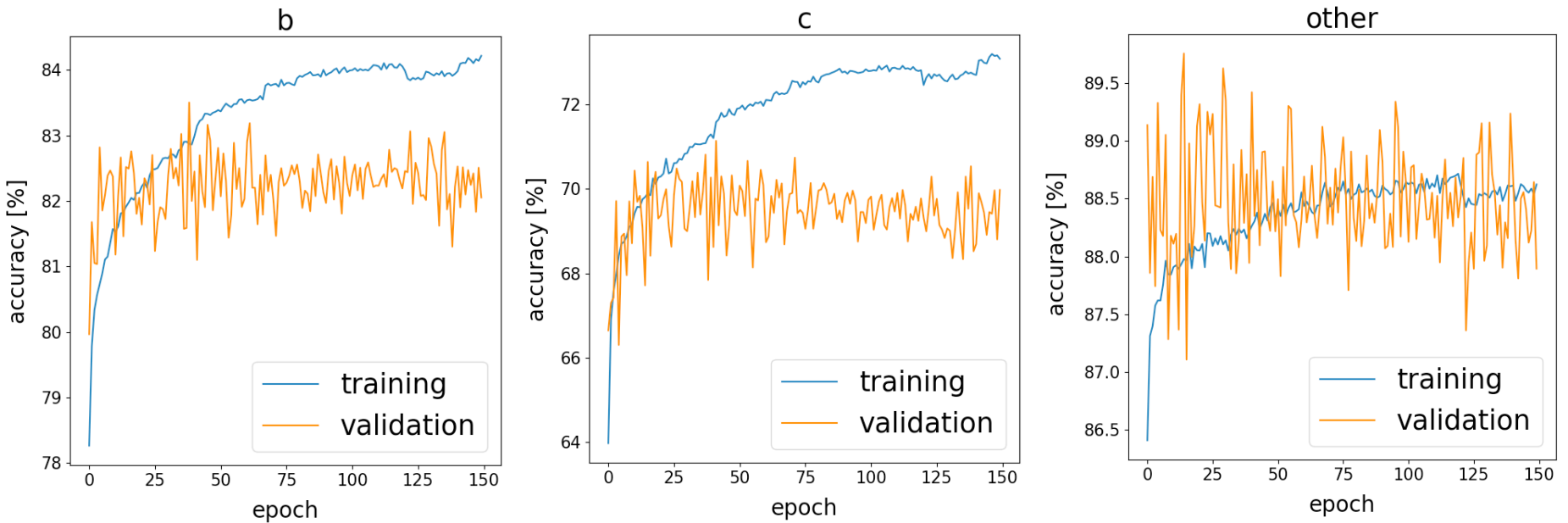
# DeepJet: loss & accuracy



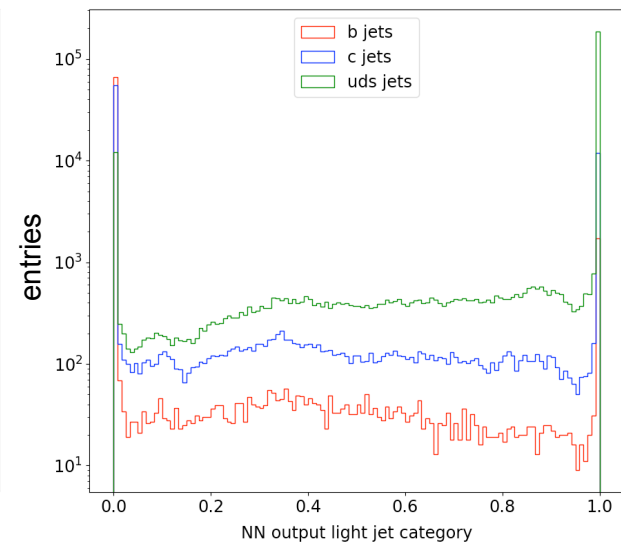
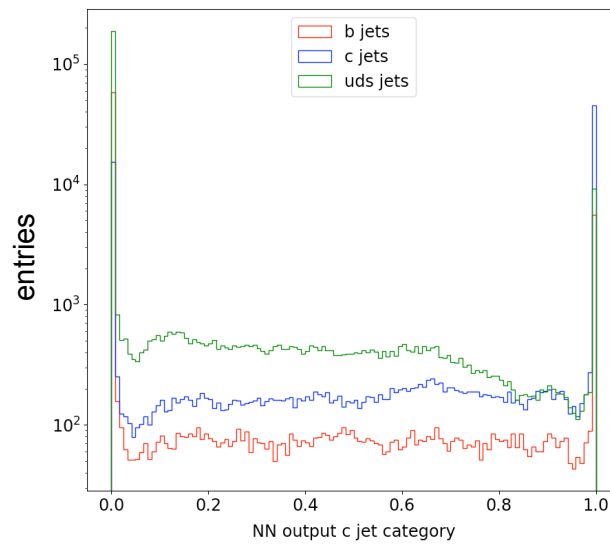
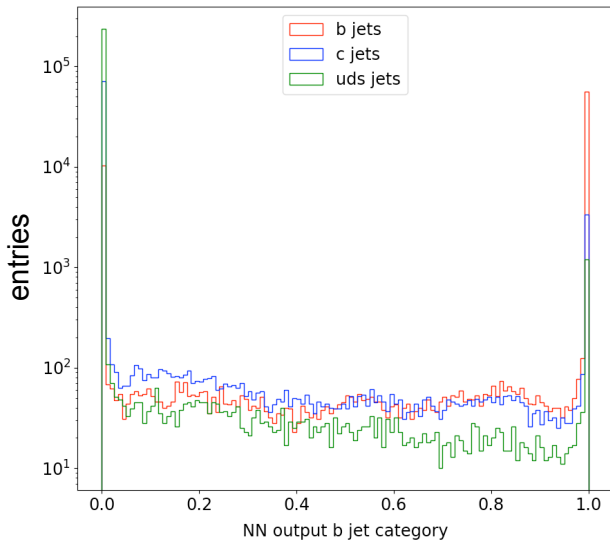


# DeepJet: loss & accuracy

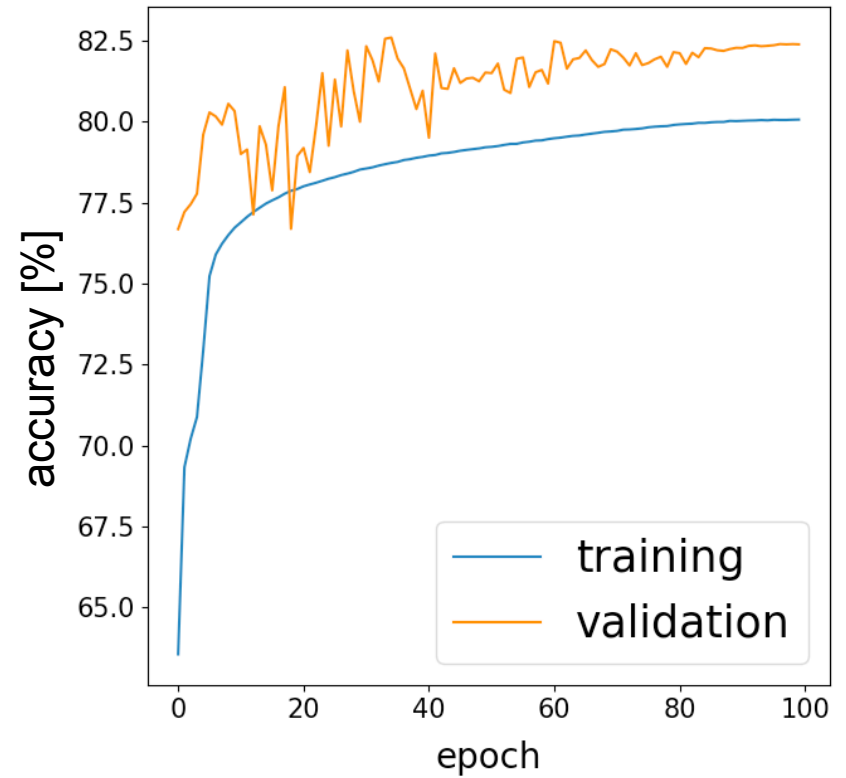
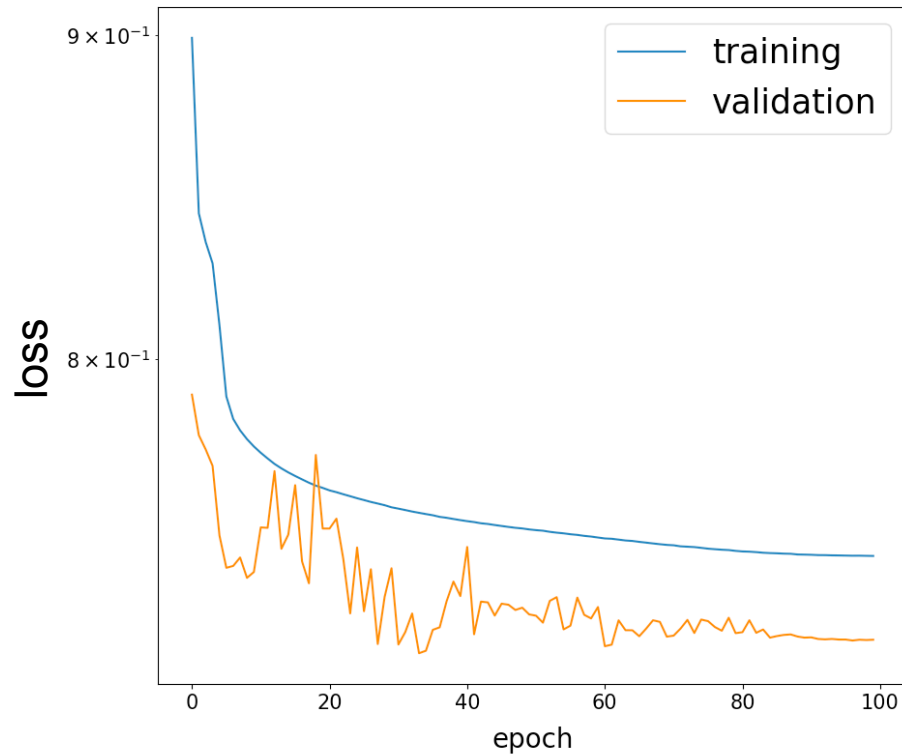
accuracy = correctly classified jets / all jets



# DeepJet: NN output

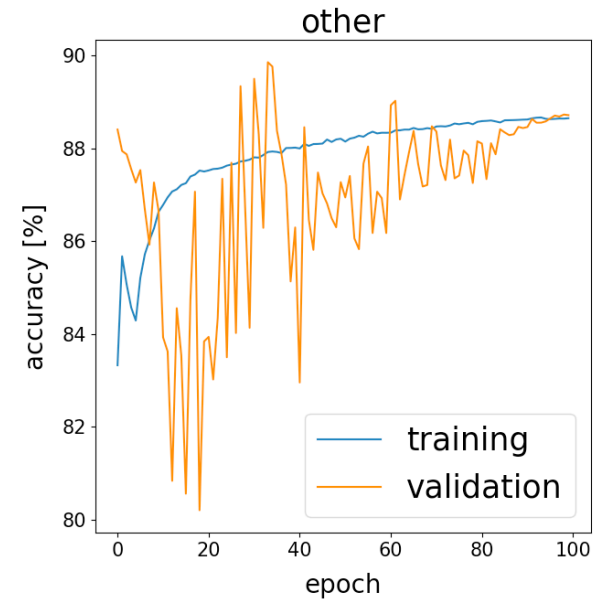
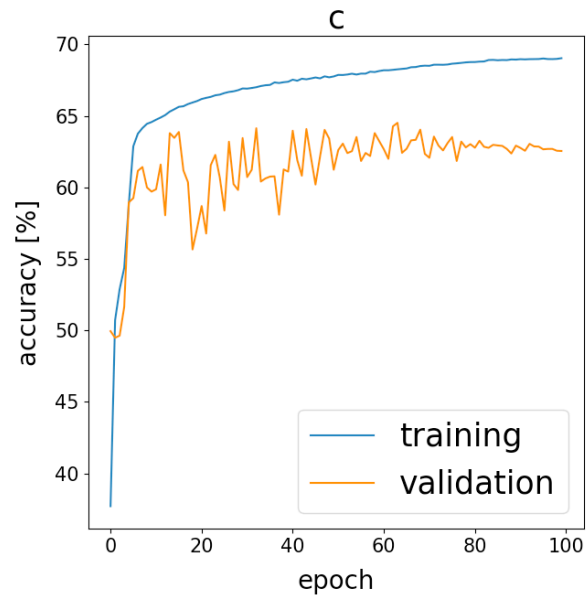
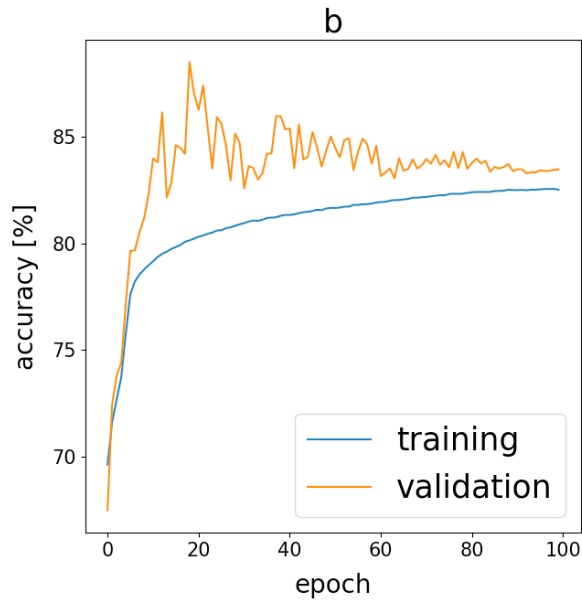


# ParticleNet: loss & accuracy

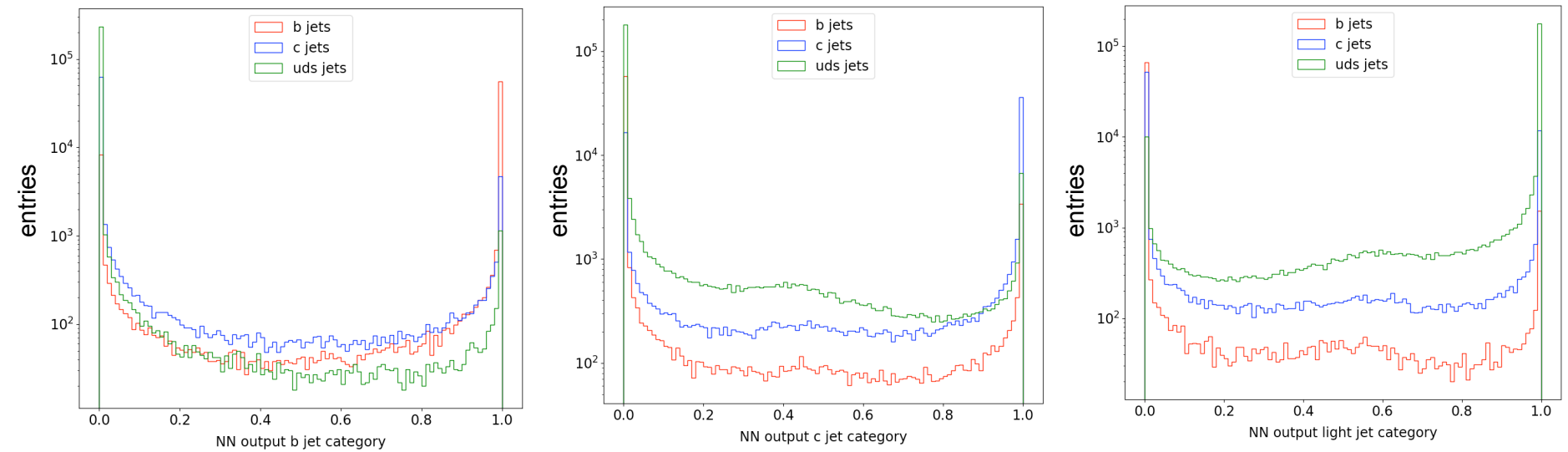


# ParticleNet: accuracies

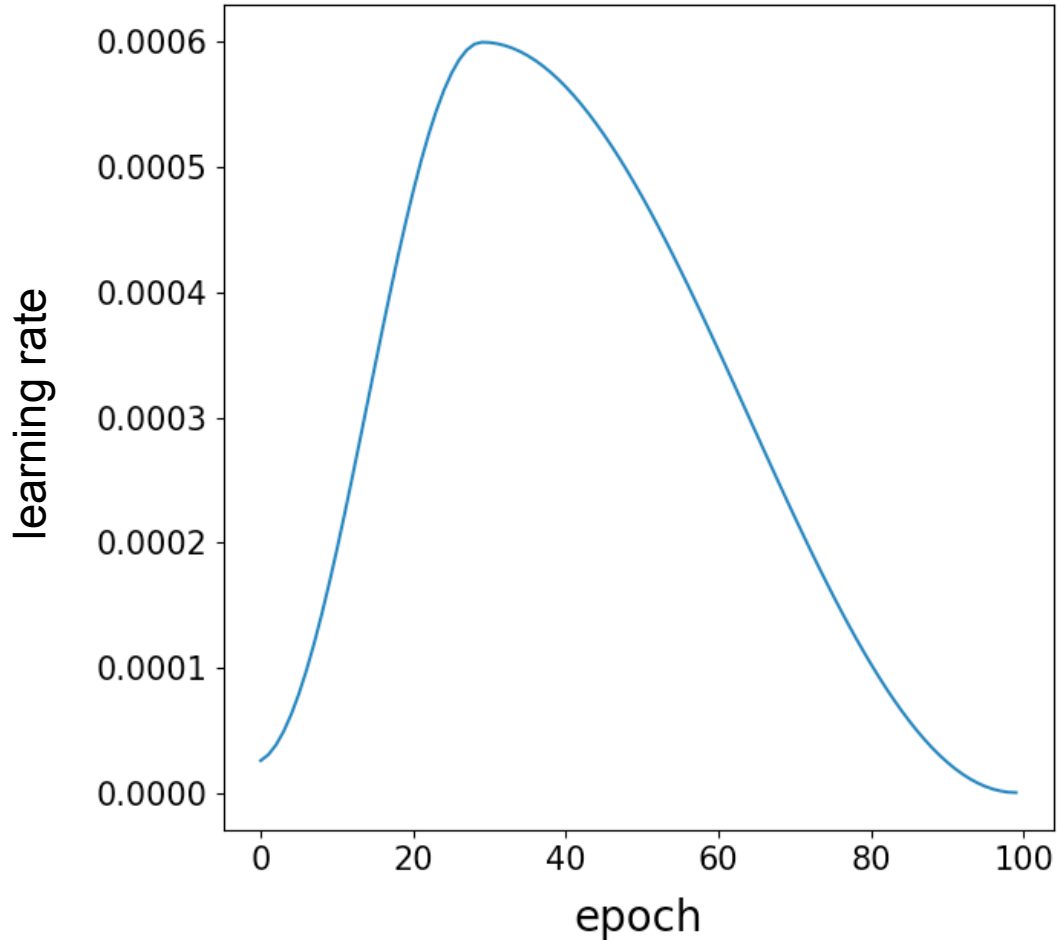
accuracy = correctly classified jets / all jets



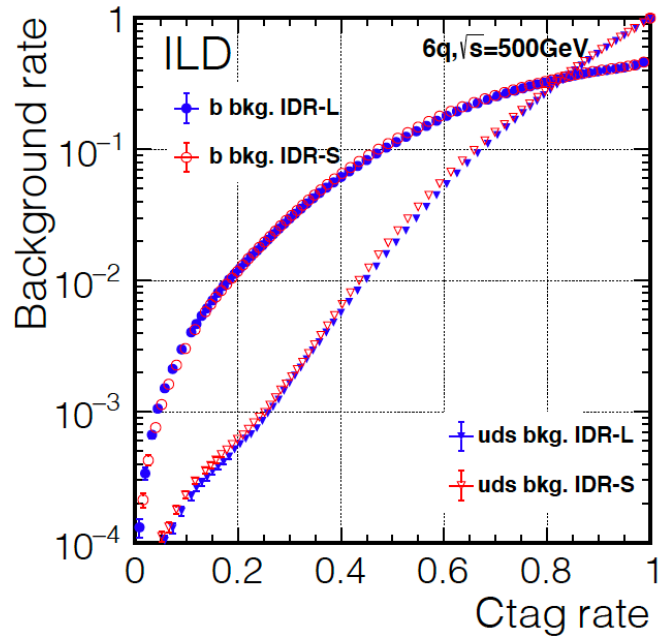
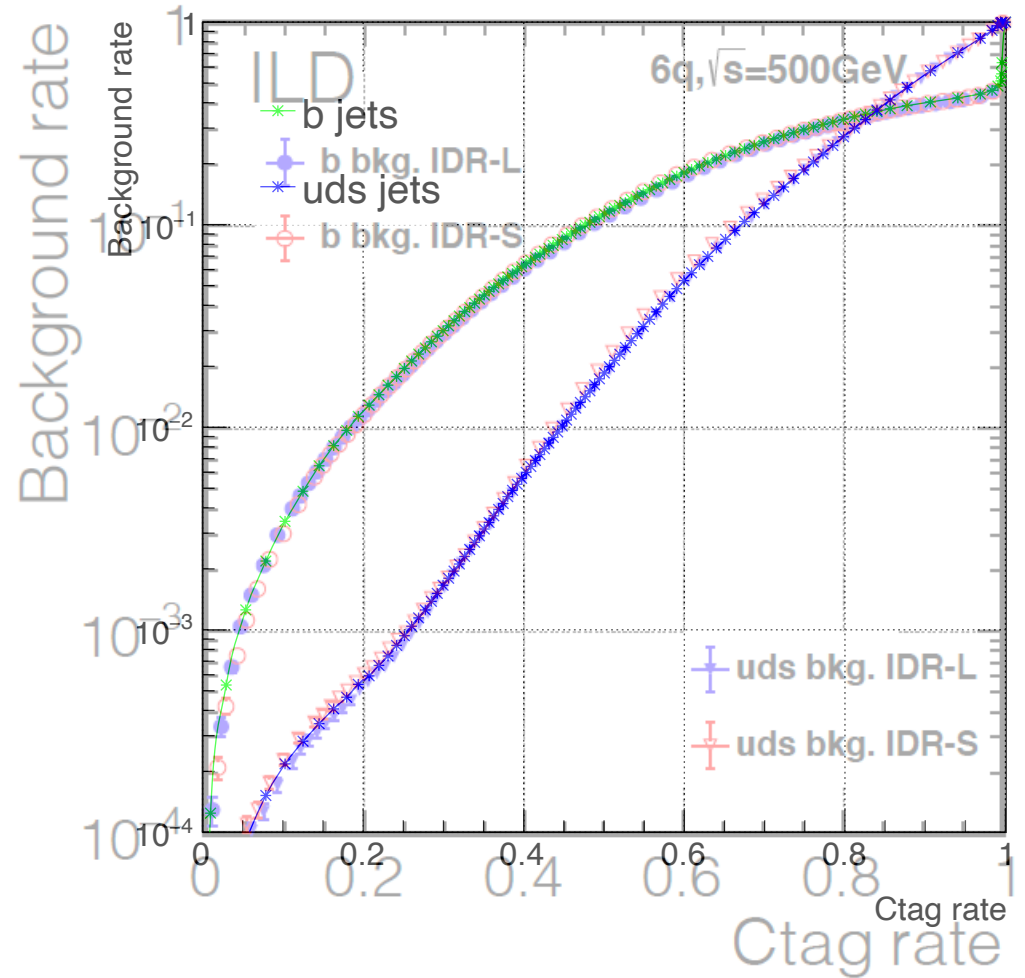
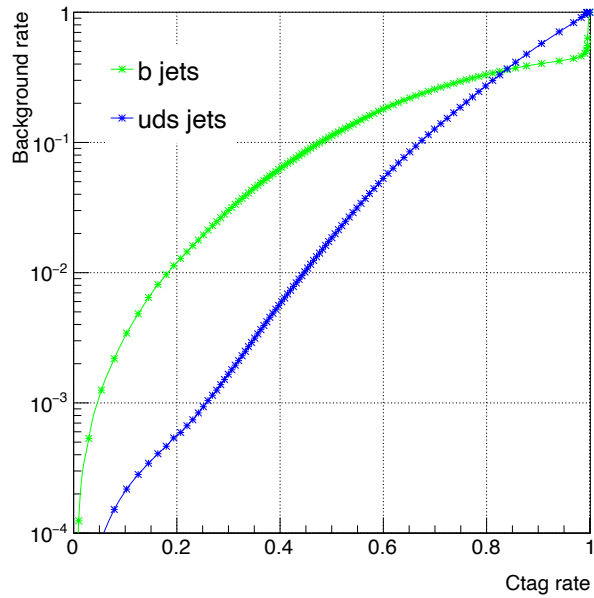
# ParticleNet: NN output



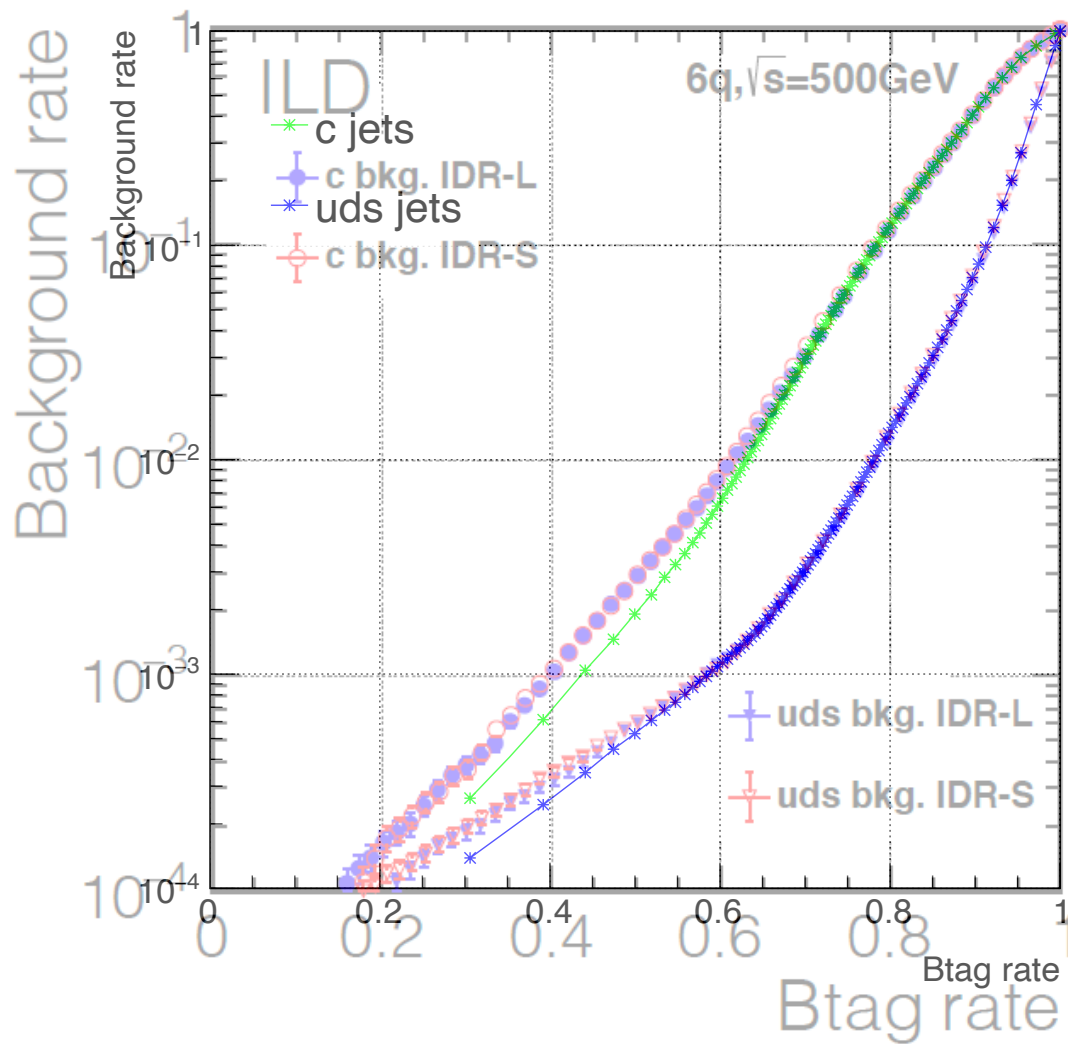
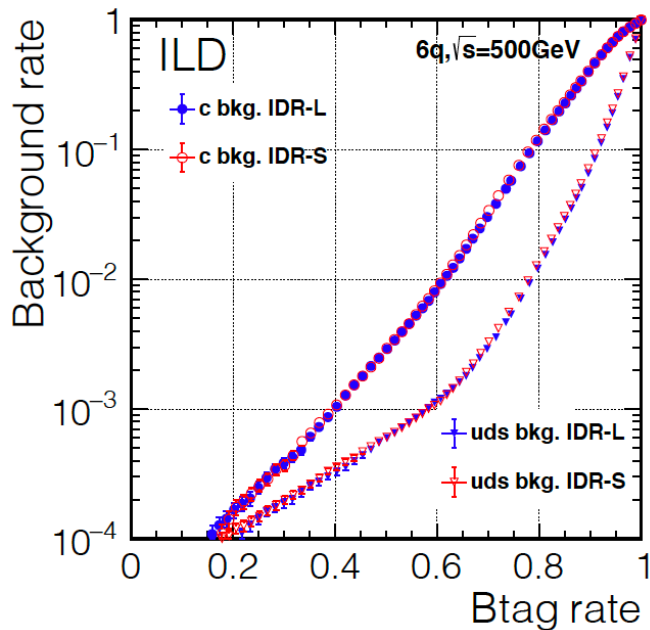
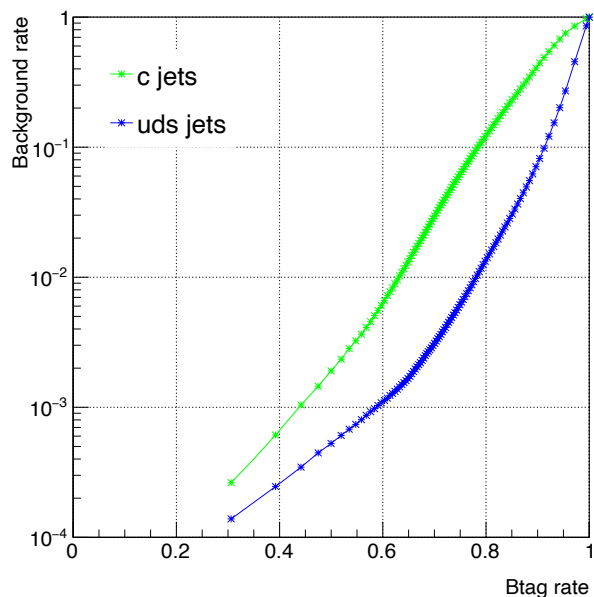
# ParticleNet: learning rate



# Performance LCFIPlus



# Performance LCFIPlus





# Variables used by LCFIPlus

Name	Description	Normalization factor	Used by category
trk1d0sig	d0 significance of track with highest d0 significance	1	A, B, C, D
trk2d0sig	d0 significance of track with second highest d0 significance	1	A, B, C, D
trk1z0sig	z0 significance of track with highest d0 significance	1	A, B, C, D
trk2z0sig	z0 significance of track with second highest d0 significance	1	A, B, C, D
trk1pt	transverse momentum of track with highest d0 significance	$1/E_{\text{jet}}$	A, B, C, D
trk2pt	transverse momentum of track with second highest d0 significance	$1/E_{\text{jet}}$	A, B, C, D
jprobr	joint probability in the r-phi plane using all tracks	1	A, B, C, D
jprobr5sigma	joint probability in the r-phi plane using all tracks having impact parameter significance exceeding 5 sigma	1	A, B, C, D
jprobz	joint probability in the z projection using all tracks	1	A, B, C, D
jprobz5sigma	joint probability in the z projection using all tracks having impact parameter significance exceeding 5 sigma	1	A, B, C, D
d0bprob	product of b-quark probabilities of d0 values for all tracks, using b/c/q d0 distributions	1	A, B, C, D
d0cprob	product of c-quark probabilities of d0 values for all tracks, using b/c/q d0 distributions	1	A, B, C, D
d0qprob	product of q-quark probabilities of d0 values for all tracks, using b/c/q d0 distributions	1	A, B, C, D
z0bprob	product of b-quark probabilities of z0 values for all tracks, using b/c/q z0 distributions	1	A, B, C, D
z0cprob	product of c-quark probabilities of z0 values for all tracks, using b/c/q z0 distributions	1	A, B, C, D
z0qprob	product of q-quark probabilities of z0 values for all tracks, using b/c/q z0 distributions	1	A, B, C, D
nmuon	number of identified muons	1	A, B, C, D
nelectron	number of identified electrons	1	A, B, C, D
trkmass	mass of all tracks exceeding 5 sigma significance in d0/z0 values	1	A, B, C, D

# Variables used by LCFIPlus

Name	Description	Normalization factor	Used by category
1vtxprob	vertex probability with all tracks associated in vertices combined	1	B, C, D
vtxlen1	decay length of the first vertex in the jet (zero if no vertex is found)	$1/E_{\text{jet}}$	B, C, D
vtxlen2	decay length of the second vertex in the jet (zero if number of vertex is less than two)	$1/E_{\text{jet}}$	D
vtxlen12	distance between the first and second vertex (zero if number of vertex is less than two)	$1/E_{\text{jet}}$	D
vtxsig1	decay length significance of the first vertex in the jet (zero if no vertex is found)	$1/E_{\text{jet}}$	B, C, D
vtxsig2	decay length significance of the second vertex in the jet (zero if number of vertex is less than two)	$1/E_{\text{jet}}$	D
vtxsig12	vtxlen12 divided by its error as computed from the sum of the covariance matrix of the first and second vertices, projected along the line connecting the two vertices	$1/E_{\text{jet}}$	D
vtxdirang1	the angle between the momentum (computed as a vector sum of track momenta) and the displacement of the first vertex	$E_{\text{jet}}$	B, C, D
vtxdirang2	the angle between the momentum (computed as a vector sum of track momenta) and the displacement of the second vertex	$E_{\text{jet}}$	D
vtxmult1	number of tracks included in the first vertex (zero if no vertex is found)	1	B, C, D
vtxmult2	number of tracks included in the second vertex (zero if number of vertex is less than two)	1	D
vtxmult	number of tracks which are used to form secondary vertices (summed for all vertices)	1	D
vtxmom1	magnitude of the vector sum of the momenta of all tracks combined into the first vertex	$1/E_{\text{jet}}$	B, C, D
vtxmom2	magnitude of the vector sum of the momenta of all tracks combined into the second vertex	$1/E_{\text{jet}}$	D
vtxmass1	mass of the first vertex computed from the sum of track four-momenta	1	B, C, D
vtxmass2	mass of the second vertex computed from the sum of track four-momenta	1	D
vtxmass	vertex mass as computed from the sum of four momenta of all tracks forming secondary vertices	1	B, C, D
vtxmasspc	mass of the vertex with minimum pt correction allowed by the error matrices of the primary and secondary vertices	1	B, C, D
vtxprob	vertex probability; for multiple vertices, the probability P is computed as $1-P = (1-P_1)(1-P_2)\dots(1-P_N)$	1	B, C, D

